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# A decomposition analysis of the relationship between parental income and multiple child outcomes<sup>†</sup>

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## Abstract

This paper explores the relationship between family income and a range of cognitive, socio-emotional, and health outcomes in mid-childhood. Child developmental outcomes are conceptualised as the result of an underlying set of associations or pathways running from distal factors (broad indicators of family characteristics and resources) to proximal factors (parental behaviours and aspects of the child's lived environment). We use a decomposition framework to systematically compare the associations underpinning the raw income gradients in the different outcomes. We find considerable variation in the extent of the income gradients, and in the factors that can account for them, across developmental domains.

**Key words:** Child outcomes; distal and proximal influences; income gradients; path analysis; multiple imputation; bootstrapping.

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## 1. Introduction

The income gradient, or the raw correlation between parental income and the outcomes of their children, is a widely used summary measure of social inequalities. For example, raw differences in educational outcomes between poor and more affluent pupils are commonly used standard statistics produced to monitor educational inequalities (e.g. Cabinet Office, 2009); income gradients in child health exist in both privately and publicly funded systems (Case *et al.*, 2002; Currie *et al.*, 2007); and there is a long literature comparing intergenerational mobility across place and time which focuses on the association between earnings or incomes of parents and children (Solon, 1999, 2002; Blanden *et al.* 2007).

The importance of this topic means research has taken a variety of approaches to understanding this relationship. One hallmark of many studies, particularly those that seek to establish causality, is a focus on a single domain of child outcomes (for example, educational achievement). This makes comparison of the size of income related inequalities in different child outcomes difficult. It also means that it is hard to compare the contribution of different factors associated with income inequality across outcomes. In this paper we address this issue directly. We examine the association between parental income and six different childhood outcomes within a unified statistical framework that allows comparison of the role of correlated parental behaviours across outcomes. The outcomes are educational performance (children's IQ and their school achievement); behaviour (their locus of control, self-esteem and behavioural difficulties) and their physical health (fat mass), all measured between the ages of seven and nine. The motivation for this approach is that child development is multi-dimensional, and it is thus important to understand which inputs that parents buy or have access to are associated with different outcomes, and the degree to which those inputs are differentially associated with parental resources.

Conceptually our approach is based on insights from ecological models of child development that distinguish distal and proximal influences on child development (Bronfenbrenner 1979, 1986). Proximal processes, which are posited as the primary drivers of development, describe the immediate environment as it is experienced by the child. Distal factors have no direct effect on children but operate only through observed and unobserved proximal processes. Income is one of a number of distal factors which are, by definition, associated with developmental outcomes via their impact on the proximal environment. We decompose the income gradients into two overlapping pathways that recognise this ordering of influences, and provide estimates of the contribution of each factor to the gradient that are

consistent with paths implied by theory. The first, proximal, pathway operates through observed parental behaviours, and their inputs into children, that vary with income. These include parenting behaviours, maternal psychosocial functioning, school quality, and measures of the home environment. The second operates through observed distal characteristics of the family that are correlated with income, and that include the education and the labour market status of parents and the neighbourhood in which the family lives.

We use a cohort data source from the UK that allows us to consider an unusually rich set of factors that both potentially influence developmental outcomes and are correlated with household income. The richness of our data means that we are able to control for many influences that are unobserved or poorly measured in other studies, such as child diet and school fixed effects. In addition, as an integral component of our estimation, we address the issue of missing data that inevitably arises when using observational data that tracks individuals over a number of years. It is particularly important to deal with these appropriately in our type of application because differing sample sizes will make the comparison of gradients across outcomes difficult to separate from variations in sample selection. We use a multiple imputation method combined with bootstrapping to derive estimates of the coefficients of interest and their distributions. We find that the magnitude of the income gradient and the proportion that can be accounted for by observed parental behaviours differs across outcomes. Whilst some behaviours are predictive of gradients in all domains, there are clear differences in the relative importance of a number of pathways. Differences in the home learning environment between low- and high-income children, and paternal learning activities in particular, are associated with greater income disparities in cognitive outcomes than in other outcomes. Income gradients in children's self-esteem and behaviour problems are much more strongly linked to maternal psychosocial functioning than are gradients in cognitive or health outcomes. Measures of children's diet at age 3 account for a larger proportion of the gradient in fat mass than in other outcomes. Our analysis also uncovers several instances in which aspects of poor children's environments may serve as protective factors that offset the influence of other risk factors. Examples are home environments that encourage greater calorie expenditure than in higher-income families, and hence reduce the risk of obesity, and lesser exposure to childcare settings associated with later behavioural problems. As in all observational studies, there is the possibility that the estimated relationships partially capture correlated unmeasured influences, and we do not claim to show causal relationships. However the evidence of very different proximal influences across the range of outcomes considered suggests there is not a single omitted

factor driving the associations with family income.

The paper is structured as follows. Section 2 presents our approach in detail and discusses it with reference to related literatures, including those that have sought to establish causality. In Section 3 we describe our data and the treatment of missing values. Section 4 presents the unconditional income gradients and alternative decompositions of these gradients. Section 5 provides a summary of key findings and a discussion of their implications.

## **2. Modelling framework**

We begin by outlining the pathway approach and defining distal and proximal influences on child development. We then present formally our statistical model and discuss the interpretation of the estimates. Finally, we compare the pathway approach to related literature which seeks to understand the role of income on child development, highlighting both points of similarity and the unique contribution of the pathway approach.

### ***2.1 Distal and proximal influences on child outcomes***

Our conceptual and methodological approach requires that each variable in our data be classified into one of two sets. The first are proximal factors that influence child development directly; the second are distal factors that have an indirect influence and operate only via some proximal mechanism. The classification of a variable is not something that can be established statistically, but comes from previous research into the child development and depends on the application in hand (Feinstein *et al.*, 2008).

In our context we make this partition in the following way. Income is the focal distal influence on children's development and impacts on children only to the extent that it affects their material circumstances and lived environments. Income is correlated with other distal factors, such as parental education and family structure, which are also important in shaping the overall proximal environment. Part of the observed income gradient reflects the role of these factors, which in this study include demographic characteristics such as family structure, maternal age and ethnicity; parental labour market characteristics; educational qualifications of the child's parents and grandparents; and aspects of the local environment captured by deprivation indices and exposure to social housing. We focus the decomposition on the income gradient because of its widespread use as a measure of social inequalities, but the method could equally be applied to the raw gradient defined by any distal factor, for example, the analysis of black-white gaps that have been the focus of much of the US literature (Fryer

and Levitt, 2006).

The income gradient we estimate here is a broader concept than the causal effect of income. The causal or ‘treatment effect’ of an increase in family income forms one component of the pathways decomposition and is what is referred to here as the direct contribution of income. This causal effect has been the subject of a great deal of research (see Section 2.4) and in that approach, distal factors other than income (such as parental education) can be thought of simply as confounders. However, the direct contribution of income is not the only component of the raw income gradient that is of interest. This gradient reflects all the distal influences in poorer children’s lives that are correlated with income and also impact on their development. Understanding the contributions of other characteristics that co-occur with low income is important for a rounded picture of the sources of the gradient.

The proximal pathways through which income and these other distal factors influence children are potentially very numerous. Two broad types of mechanism have been proposed in the literature and our rich data allow us to include measures to examine both mechanisms. The first is the financial capital or investment model, which posits that poverty affects child development because it hampers parents’ ability to purchase the materials, experiences and services that are conducive to successful development (Bradley and Corwyn, 2002; Becker and Tomes, 1986). This mechanism is operationalised here with measures of the physical home environment (such as whether it is clean and safe); measures of cognitively stimulating materials in the home environment (such as books and CDs) and of stimulating parental behaviours (such as the frequency the child is read to and taken to museums); and measures of childcare mode and intensity. The second is the family process perspective, which argues that income impacts on non-material parental resources, such as the way parents monitor their children and respond to their needs (Elder and Caspi, 1988; Conger *et al.* 1992; McLoyd, 1990). Key factors emphasized by this perspective are perceived financial strain, parental psychological well-being and the warmth and sensitivity of parent-child interactions. Finally, whilst in our data we observe an unusually rich variety of proximal factors, substantial unobserved influences are likely to remain. The effect of these unobserved proximals will be partially picked up by the included variables to the extent they are correlated, and the importance of orthogonal unobserved factors is quantified by the portion of the income gradient that remains unexplained by the set of observed proximal variables.

## **2.2 Statistical method**

Our decomposition of the income gradient builds on path analysis methods that have a

long history in the social sciences (Bollen, 1989). The method allows the researcher to express the overall income gradient as the sum of a number of ‘pathways’, which are built up from a set of underlying regressions specifying the nature of the relationships between income, other distal factors, proximal factors, and developmental outcomes. The approach has clear parallels with graphical chain modelling and, in common with that approach, can be viewed as a form of structural equation modelling in which simplifying assumptions are made about the structural equations in order to avoid the computational problems that arise when fitting a single complex model to very high-dimensional data (Berrington *et al.*, 2008, provides further discussion in a graphical chain modelling framework). A number of studies have used more restricted versions of the method presented here (Blanden *et al.*, 2007; Goodman *et al.*, 2011; Waldfogel and Washbrook, 2011). The current analysis extends the methods used in these latter papers by distinguishing analytically between distal and proximal variables, constructing estimates of the standard errors for the path coefficients, dealing with missing data in a consistent and sophisticated way and allowing comparison across multiple domains of child development.

We define the unconditional income gradient in the  $Y^{\text{th}}$  developmental outcome of the  $i^{\text{th}}$  child,  $Y_i$  ( $i = 1, \dots, N$ ), as  $\delta$  from the regression of  $Y_i$  on the log of family income ( $X_i$ ):

$$Y_i = \delta X_i + e_i \quad (1)$$

where  $e_i$  is a residual error term uncorrelated with log income. In what follows we set out the underlying structural equations and show how they combine to give a disaggregated expression for  $\delta$ .

[---FIGURE 1 HERE---

The underlying path model is expressed diagrammatically in Figure 1, where arrows are used to denote the dependent and independent variables in each equation. They are not intended to imply a causal relationship. The path coefficients are defined according to the following set of equations:

$$Y_i = \boldsymbol{\gamma} \mathbf{P}_i + \boldsymbol{\theta} \mathbf{D}_i + \pi X_i + \mu_i \quad (2)$$

$$\mathbf{P}_i = \boldsymbol{\beta} \mathbf{D}_i + \boldsymbol{\lambda} X_i + \boldsymbol{\eta}_i \quad (3)$$

$$\mathbf{D}_i = \boldsymbol{\alpha} X_i + \mathbf{v}_i \quad (4)$$

where  $\mathbf{P}_i$  is an  $m \times 1$  vector of proximal variables;  $\mathbf{D}_i$  is an  $n \times 1$  vector of distal variables other than income;  $\boldsymbol{\gamma}$ ,  $\boldsymbol{\theta}$ ,  $\boldsymbol{\beta}$ ,  $\boldsymbol{\lambda}$  and  $\boldsymbol{\alpha}$  are  $1 \times m$ ,  $1 \times n$ ,  $m \times n$ ,  $m \times 1$  and  $n \times 1$  matrices of coefficients respectively;  $\pi$  is a scalar coefficient;  $\boldsymbol{\eta}_i$  and  $\mathbf{v}_i$  are vectors of residual error terms

and  $\mu_i$  is a scalar residual error. The path analysis approach requires that the errors in each of the  $(m + n + 1)$  structural equations be conditionally independent of the explanatory variables (Bollen, 1989). If this assumption is valid then the coefficients can be consistently estimated by ordinary least squares regression. We use a non-parametric bootstrap method to conduct statistical inference on these OLS point estimates, which means no restrictions are placed on the marginal or joint distributions of any of the error terms.

Equation 2 specifies the child outcome as a function of all the variables in the model. Our assumption is that income, and other distal factors, are associated with the outcome solely via their association with proximal processes.  $\mathbf{D}_i$  and  $X_i$ , therefore, are included in equation 2, not as direct determinants of the child outcome, but rather as proxies for unobservable proximal factors that may be correlated with the observed factors  $\mathbf{P}_i$ . The inclusion of  $\mathbf{D}_i$  and  $X_i$  is to mitigate omitted variable bias in the estimates of  $\boldsymbol{\gamma}$ , given that the  $\boldsymbol{\gamma}$  are identified from differences in observed proximal factors between children from equivalent family backgrounds. Large and significant estimates of  $\boldsymbol{\theta}$  and  $\pi$  imply that there are systematic differences in the unobserved proximal influences on the outcome between children from different social backgrounds. Note the effect of a given proximal variable on the outcome is estimated conditional on all other observed proximal variables.

There are several key threats to consistency of the estimates in equation 2. One is that, even conditional on the distal variables, unmeasured proximal processes are correlated with the included proximal measures. If this is the case then the pathway attributed to a particular proximal variable will partially pick up the contribution of the correlated unmeasured factor. This form of bias is minimised by the richness of the proximal variables observed in our data and included in the model. A second source of bias is reverse causation, by which the child outcome itself influences parental behaviour. We reduce the risk of this problem by the timing of our measured variables. We use explanatory variables that are measured in the preschool period only; is at least two years (and often more) before the outcome is observed. There still remains the possibility that the endowments with which the child is born (often referred to as innate ability in the cognitive setting) are correlated with the proximal variables. This could arise, for example, if parents observe the child's endowment and adapt their behaviour accordingly. Our focus on descriptive decompositions that can be compared across outcomes precludes the use of techniques to address this problem directly (discussed briefly in Section 2.4). Hence the role of parental response to inherited characteristics needs to be borne in mind when interpreting our results.



Equation 3 embodies the assumption that the environment that parents are able to provide for their children reflects the constraints imposed by their socio-economic resources, of which income is only a part. The matrix of parameters  $\beta$  in equation 3 captures the net association of each distal variable other than income with each proximal factor, while the parameter vector on income,  $\lambda$ , captures the conditional association of income and the proximal factors, controlling fully for other distal variables. Again, correlation between the unmeasured determinants of each proximal factor and the distal predictors will invalidate the conditional independence of the error terms. Perhaps the key characteristic of concern here is parental cognitive ability, which is not measured in our data. We expect that the influence of this factor will load heavily onto the estimated parental education coefficients, so these should not be interpreted as the causal effect of qualifications.

Equation 4 closes the system (see also Figure 1) as it captures the unconditional association between each distal factor and income. The degree to which a given distal factor matters for the income gradient depends on how strongly it is correlated with income. A factor may be consequential for child development but if it does not co-vary with income it cannot help to explain why low-income children have poorer outcomes than their more affluent counterparts. The parameter vector  $\alpha$  captures the strength of these associations: it is simply a set of raw correlations, scaled appropriately.

Substitution of equations 3 and 4 into equation 2 allows us to write the decomposition:

$$\begin{aligned} Y_i &= (\gamma\beta\alpha + \gamma\lambda + \theta\alpha + \pi)X_i + (\gamma\eta_i + \theta v_i + \mu_i) \\ &\equiv \delta X_i + e_i \\ \therefore \delta &\equiv \gamma\beta\alpha + \gamma\lambda + \theta\alpha + \pi \end{aligned} \tag{5}$$

The unconditional income gradient,  $\delta$ , can be written as the sum of four types of ‘path’ coefficient, each of which represents a different pathway from income to an outcome,  $Y$ , in Figure 1. As equation (5) makes clear, a path coefficient is the product of the partial effects of one variable on another. These path coefficients can be combined in different ways to give alternative decompositions of the income gradient.

The  $(m + n + 1)$  variables entering the structural equations 2 to 4 are a mixture of binary, categorical and continuous variables. Linear regression (or probability) models are used to estimate all the equations in order to preserve the adding up property shown in equation 5. For categorical variables a reference category is omitted entirely from the model and the remaining categorical indicators are treated as binary. Point estimates of the

parameters in equations 2 to 4 are estimated using equation-by-equation OLS and the estimates are stacked into matrices and combined according to equation 5. Standard errors for the combined path coefficients are estimated by a non-parametric bootstrap with 200 repetitions, which removes the need to make any assumptions about the joint distribution of the residual errors. Each repetition re-samples (with replacement) from the original dataset, estimates the  $m + n + 1$  ordinary linear regressions given in equations 2 to 4, and calculates the nonlinear combinations of the coefficients. This method produces 200 estimates of each path coefficient which together give the sampling distribution of the population parameter. We take the mean as the point estimate of the coefficient and the standard deviation as its standard error.

The entire decomposition process is repeated separately for each of the six child outcome variables. Item non-response is addressed through multiple imputation. This is discussed more fully in Section 3.3, but briefly the process described above is repeated 10 times, each on a different imputed dataset, and the 10 sets of estimates are then combined using Rubin's rules. For tractability our decomposition approach relies on the identifying assumptions that the effects of different factors on the outcome are linear and additively separable. We tested the sensitivity of our findings to the linearity assumption by recoding continuous variables into sets of discrete categorical variables and re-running the analysis. The results were virtually unchanged. However, if there are non-trivial interaction effects between multiple factors this will be missed by our model.

### ***2.3 Interpreting the estimates from the model***

We now show how combinations of the path coefficients in equation (5) can be used to quantify different aspects of the associations underlying the raw income gradient. One decomposition focuses on the contribution of the proximal factors to the overall gradient, without disaggregating by different distal pathways. The component  $\gamma(\beta\alpha + \lambda)$  gives the income gradient we would predict purely on the basis of differences in observed proximal factors between low- and higher-income families. The remaining gradient  $(\theta\alpha + \pi)$ , therefore, is the part that can only be accounted for by differences in unobserved proximal factors, or the gradient predicted to remain if all observed proximal factors were equalized across families. Using a  $j$  subscript to distinguish scalars or vectors related to the  $j$ th proximal variable, we can further break out the term  $\gamma_j(\beta_j\alpha + \lambda_j)$ , or the contribution to the gradient of differences in the  $j$ th proximal factor, holding all else equal.

A second decomposition breaks down the overall gradient into components associated with correlated distal factors,  $(\gamma\beta + \theta)\alpha$ , and a residual ‘direct’ contribution of income  $(\gamma\lambda + \pi)$ . This formulation combines together all observed and unobserved pathways through which a distal factor influences the outcome. The first term provides estimates of the gradient that would be predicted to exist on the basis of other family characteristics, even if income were held constant. Conversely, the direct contribution of income is the gradient predicted to remain if all distal characteristics were equalized across families while incomes were left unchanged; perhaps the closest approximation to an overall causal effect of income we get in this descriptive framework. It can be further broken down into pathways running directly from income through different proximal factors to the outcome,  $\gamma_j\lambda_j$ , and a final unexplained residual,  $\pi$ , that represents the gradient predicted to remain even if all proximal and distal variables in the model were equalized. Online appendix 2 presents a worked numerical example of the alternative decompositions for a very simple hypothetical model.

#### ***2.4 Relationship of the pathway modelling approach to other methodologies***

We now discuss the advantages and disadvantages of the pathways approach relative to others which examine the impact of income on child development. Early work in economics focused on estimation of the ‘reduced form’ effect of income i.e. the association between income and outcomes when other confounding characteristics are controlled (Duncan and Brooks-Gunn, 1997; Klebanov *et al.*, 1998; Dearing *et al.*, 2001). These estimates correspond to the composite  $(\gamma\lambda + \pi)$  in the pathways approach, which we label the direct contribution of income. Concern that conditional reduced form estimates did not accurately reflect the causal effect of income led to a focus on adjusting for unobserved heterogeneity. One approach is to exploit variation induced by an experimental intervention or a policy shift. Such studies normally only consider a limited range of outcomes (often a measure of educational attainment). In addition, experimental studies rarely involve *only* changes in incomes as they usually also involve some desired behavioural response. For example, the Minnesota Family Income programme and the Canadian Self-Sufficiency Programme sought an increase in employment among lone mothers (Grogger and Karoly, 2005) and cash programmes in many developing countries regularly link the payment to child school attendance (e.g. Baez and Camacho, 2011; Skoufias *et al.*, 2001). On the other hand, quasi-experimental interventions involve a policy shift which result in income gains for a particular group and the effects on child outcomes can be compared to a non- or less treated group (for example, Dahl and Lochner, 2012; Milligan and Stabile, 2011; Gregg *et al.*, 2009). The

strength of these studies is they provide estimates of a causal local treatment effect, but they do not generally explore the channels through which the effects occur, and the policy changes underlying them tend to involve relatively modest income changes, for a limited part of childhood and for selected groups.

The channels have, however, received attention in mediation studies in the developmental psychology literature. Studies such as Guo and Harris (2000), Yeung *et al.*, (2002) and Schoon *et al.*, (2010) use structural equation models to test theories of the way in which income is mediated. These studies exploit the kind of rich observational data we use here. Typically their focus has been on understanding the processes that explain the conditional effect of income only, so their findings correspond to the part of our decomposition that breaks the direct contribution of income into various explained ( $\sum_j \gamma_j \lambda_j$ ) and unexplained ( $\pi$ ) components.

An approach from the economics literature that seeks to get inside the ‘black box’ of the family background-child outcome association is the estimation of human capital production functions, for example, Todd and Wolpin (2003, 2007), Ermisch (2008), Cunha *et al.*, (2010). This approach views child development as a production process and aims to estimate the technology by which inputs are transformed into outputs. In common with the ecological approach employed here it posits that certain factors are the direct determinants of human development, and in that sense inputs are conceptually equivalent to proximal processes. Equation 2, which expresses the outcome as a function of all distal and proximal processes, can be viewed as a simple ‘hybrid’ production function in which distal factors are included to proxy for unobserved inputs (Todd and Wolpin, 2007). A key insight from this approach is that child cognitive attainment reflects the dynamic interaction between the child’s innate ability and the cumulative effect of a series of investments made over the life of the child. Our simple production function is a static approximation to these more complex structural models that attempt to estimate the entire dynamic relationship between inputs and the outcome as it evolves over the child’s life cycle (Cunha *et al.*, 2010).

A key criticism of static, cross-sectional estimates of the production function is that they overstate the importance of contemporaneous input measures because of their correlation with omitted historical inputs. To try to overcome this, here our proximal measures are not only measured prior to the outcomes but are, in many cases, composite measures from multiple waves of data spanning all the preschool years (see Section 3 and Appendix Table 1). They can be viewed as summary measures of the whole history of inputs

during that period. We also do not employ a value-added specification, in which lagged outcome measures are included as controls, so the associations we measure in equation 2 capture any effects of the proximal processes that are transmitted via their impact on intermediate outcomes. In general, it is not our aim to model the full dynamic process of child development, but to understand the income gradients as they stand in a particular snapshot of childhood.

### **3. Data**

We use a rich cohort data set which contains measures that are frequently collected in surveys of childhood experiences (such as cognitive stimulation in the home, maternal depression and discipline style) but also includes measures that are less frequently observed (for example, the child's diet and school identifiers). We also match to administrative data.

#### ***3.1 The Avon Longitudinal Study of Parents and Children (ALSPAC) cohort***

We use a birth cohort of English children, ALSPAC, which recruited pregnant women, resident in the Avon area of England, whose expected date of delivery fell between 1<sup>st</sup> April 1991 and 31<sup>st</sup> December 1992. The enrolment sample consisted of 14,541 women (between 80 to 90 percent of all those who had a pregnancy during this period), of which 13,801 (95%) went on to become the mothers of surviving offspring at 12 months, with multiple births leading to a total of 13,971 children in the study at that age. The Avon area has a population of 1 million and includes the city of Bristol (population 0.5 million), and a mixture of rural areas, inner city deprivation, suburbs and moderate sized towns. Comparison with the 1991 census showed that the sample is broadly representative of the national population of mothers with infants less than 1 year of age (Boyd *et al.*, 2013 provides further details).

Study families were surveyed with high frequency from the time of pregnancy onwards. For example, mothers completed 4 postal questionnaires prior to the birth, a further 5 on family characteristics, and a further 8 focusing on the study child in the first 4 years after the birth alone. The study also contains data from a number of other sources. Three clinical assessment visits took place when the children were 7, 8 and 9 years of age, where children were administered a range of detailed hands-on physical, psychometric and psychological tests. We use a number of external sources of information that have been matched to the ALSPAC children. These are records from the National Pupil Database (NPD), which contains school identifiers and results on national (Key Stage 1) school tests for all children

in the state school system, and information on local deprivation at the small area level (Indices of Multiple Deprivation, IMD).

ALSPAC has certain advantages for our purposes over other national birth cohort studies. Some outcome variables measured directly during the clinical assessment visits (such as locus of control and fat mass) are not available in other studies or are measured more crudely. Many explanatory variables are measured at multiple developmental stages in early childhood including, uniquely, the period when the child was in utero. In addition, the regional census nature of the sample allows us to exploit the fact that multiple study children are nested within the same schools.

### **3.2    *Analysis variables***

The variables in our analysis fall into one of four types: outcomes measures, income, other distal factors and proximal factors. This section gives a brief introduction to the data used. Full details of the construction of all variables and source references and descriptive statistics are in online appendix Tables A1 and A2.

*Outcome measures.* We explore the income gradients in six different measures of developmental outcomes when the child is aged between seven and nine. Two of these are cognitive: IQ at eight (the WISC-III UK) and Key Stage 1 (KS1) scores at seven. The latter are scores from national school tests of reading, writing and mathematics and are from national administrative data (the National Pupil Database, NPD). While the two are strongly related, we argue that IQ can be thought of more as a measure of ‘pure intelligence’ whereas Key Stage 1 is more a measure of performance in school-based literacy and numeracy tests.

Three are ‘non-cognitive’ outcomes: locus of control at eight; self-esteem at eight; and behaviour problems at seven. Individuals with an ‘external’ locus of control tend to attribute outcomes to luck, chance, fate, or the interventions of others, whilst those with an ‘internal’ locus of control tend to believe that their own efforts are a decisive influence. ‘Internal’ individuals are expected to be more active in pursuing goals and to show greater ingenuity and persistence when confronted with obstacles than ‘external’ individuals. Locus of control and self-esteem are taken from scales completed in person by the child during an ALSPAC clinic. Behaviour is measured by teacher-rated scores on the well-known SDQ Total Behavioural Difficulties Scale. Unlike studies that use mother-reported behaviour scores, therefore, our measure is not subject to the potential biases arising from the fact that mothers report both the explanatory variables and the outcome (e.g. Fergusson *et al.*, 1993). We note, however, that children’s behaviour in school may be systematically different from

their behaviour at home, and the potential for teacher bias (e.g. Johnston *et al.*, 2012). To the extent that the latter occurs at the school, rather than at the individual, level it will be mitigated by our use of controls for the school which children attend (discussed below). The final measure is a physical health outcome: fat mass at age nine. This is derived from full body (DXA) scans and is an indicator of risk of obesity, which is superior to body mass index (BMI) as the scans distinguish between lean muscle and fat (Power *et al.*, 1997).

All six measures of child outcomes are normalized on child sex, cohort year and month of birth, then standardized to mean 100, standard deviation 10, on the full sample of children with non-missing values for that outcome. The original locus of control, behaviour and body fat measures are all such that higher scores indicate more adverse outcomes. We estimate models using these original variables, but to facilitate comparison we reverse the sign of the coefficients for these outcomes in the presentation of our results. Hence in all cases a coefficient of 1 on an explanatory variable is associated with an improvement of one-tenth of a standard deviation in the given outcome, where that standard deviation relates to all valid observations (see below). Pairwise correlations between the outcomes (online appendix Table A3) range from 0.64 for IQ and KS1 to 0.02 for self-esteem and fat mass. The mean of the 15 outcome correlations is only 0.22, which provides support for the idea that child well-being is multi-dimensional and not summarised well by only one or two outcome measures.

*Income.* Our measure of family income is constructed from banded information on weekly disposable household income taken from two questionnaires at child age 33 and 47 months (the only two dates at which it is available in early childhood). We average over the two measures to reduce measurement error and use the log. This specification embodies the insights from previous work (e.g. Dearing *et al.*, 2001; Duncan *et al.*, 2010) that the relationship between income and child development is non-linear.

*Distal factors.* We consider four groupings of distal variables that capture other dimensions of a family's socio-demographic resources. They are: household demographics (family structure, family size, maternal age and race/ethnicity); labour market status (parental employment and occupation); education (parents' and maternal grandparents' highest qualifications); and neighbourhood (local deprivation and social housing). The variables representing family structure, siblings and parental employment summarise the pre-natal to 47 months post-birth period. For example, the categorical maternal employment variable distinguishes mothers who worked full-time at any point between birth and 47 months; those who worked part-time only during this period; and those who did not work at all. Social housing is similarly captured by a composite variable that uses information up to 33 months

post-birth. Parental education and occupation were measured during pregnancy and the local area is location at birth.

*Proximal factors.* Proximal variables are organized into a number of groupings. These are maternal psychosocial functioning; pre-school childcare mode; health behaviours and health at birth; home learning environment; physical home environment; and school composition and quality (see appendix Table A1). Wherever possible we have included proximals used in previous research. For example, our measures of the home learning environment – cognitively stimulating materials and activities – are standard in research on the relationship between family background and child outcomes, and correspond closely to a number of items from the widely-used Home Observation for the Measurement of the Environment (HOME) scale. They include ownership of books and toys; maternal teaching of 10 items such as shapes, colours and the alphabet; frequency of reading and singing to the child by the mother and her partner; and trips to places such as libraries and museums. Measures are constructed from information collected at four waves between 6 and 42 months and are designed to capture both timing and intensity of experiences over the preschool period. As another example, while we do not have measures of the quality of childcare, we have very detailed data on type of childcare and hours of care, for 6 dates between 8 weeks and school entry. We construct 12 non-mutually exclusive categorical variables measuring exposure to six types of care for the period 0 to 2, and for the period 3 to school entry. Each variable has three categories for whether the child attended that type of care, not at all, less than 15 hours a week or 15+ hours per week, giving a set of 24 childcare indicators.

We also expand the set of potential proximal variables beyond those used in previous studies. Specifically, we widen the scope of maternal psychosocial functioning beyond depression and subjective financial pressure to include measures of the frequency and severity of shocks experienced by the household; the quality of the parental relationship; the extent and depth of the mother's social networks; and the mother's locus of control. Again, the majority of these variables combine information from multiple time points between pregnancy and 47 months. We include measures of breastfeeding and child's diet at age three as additional health-related factors, and other dimensions of the physical home environment such as crowding, noise and access to a car or garden.

A final innovation is that the geographical nature of the ALSPAC cohort allows us to explore the contribution of schools in a very flexible way. We use school dummies as explanatory variables to capture the effect on scores of attendance at a particular school, relative to the reference school. This use of school fixed effects captures the contribution of



all factors common to a given school, including peer group composition, school resources and the quality of teaching.

### 3.3 *Missing data*

Missing data problems will occur in any analysis of longitudinal cohort data that uses a very large number of variables, because of attrition and item non-response. These problems are particularly acute in ALSPAC because of the very high frequency of follow-up of cohort members. While many birth cohorts will have administered just two or three survey instruments by the time the cohort members are 9, in ALSPAC the number is closer to 50. Non-monotone non-response is very common in ALSPAC, as respondents often miss one or more follow-ups but do not leave the study completely. Our target sample is the 9,476 children with some information on income and at least one outcome measure. The target sample as a whole is slightly positively selected in relation to the initial sample of 13,971 in terms of observable characteristics. Using maternal education (available for virtually the whole cohort) as an indicator of socio-economic status, 35% of the initial sample have age 18 (A-levels) school qualifications or higher compared with 39% of our target sample.

Within the target sample item non-response on the outcome measures varies across outcomes. The largest sample at 8,727 is for the Key Stage 1 scores, as these are matched into ALSPAC from administrative data. The smallest sample is for behaviour problems (3,294), which are teacher assessed and results from the fact that not all teachers completed the relevant questionnaire. Even without taking into account any missingness in the 160 explanatory variables, only 1,645 observations have complete data on all six outcomes, and this sample is highly non-representative (for example, 50% of the common sample have mothers with an A-level qualification or above). Full details in the proportion of missing data for all the analysis variables are provided in appendix Table A2.

To exploit all the information contained in the sample we used multiple imputation by chained equations (van Buuren *et al.*, 1999). Our imputation model used all the variables that enter the analysis models and produced ten 9,476-observation rectangular datasets using the Stata command *ice* (Royston, 2004). The multiple imputation method relies on the assumption that data are missing at random (MAR), given the known characteristics of the missing individuals. While this assumption is essentially untestable we believe it appropriate in this case because of (a) the high degree of non-monotone non-response that provides later data to impute earlier missing values, (b) the rich nature of the data included in the imputation and analysis models, (c) the availability of the NPD data which provides school

achievement information for virtually the whole sample towards the end of the analysis period, and (d) our models are linear and do not contain any interaction effects that commonly lead to violation of the MAR assumption.

The bootstrap estimation procedure described in Section 2.2 was conducted separately on each imputed dataset, yielding ten sets of estimates of the path coefficients and their standard errors (the means and standard deviations of the 200 values given by the bootstrap). These ten values were then combined using Rubin's rules to yield our final estimates. The significance of each path coefficient was calculated by comparing the ratio of the coefficient to its standard error with a standard normal distribution using a two-tailed test.

## 4. Results

### 4.1 *The income gradients*

We begin by presenting the raw income gradients. Figure 2 shows these for the six outcomes, estimated as the  $\delta$  from equation 1. All gradients are significant at the 1% level, and show that the poorest children fare less well than their better-off peers. The gradient is largest for cognitive outcomes, where a unit change in (log) income is associated with an increase in IQ of 6.6 points (or 0.66 of a standard deviation), and a marginally smaller increase in academic achievement scores (Key Stage 1). The gradients in non-cognitive outcomes are around a third to a half as large as those in cognitive outcomes, with the steepest gradient in locus of control and the shallowest in self-esteem, and with behavioural problems falling somewhere between the two. The gradient in fat mass is the smallest of all six outcomes at around 1.6 points (0.16 of a standard deviation). The finding that it is cognitive development that is most strongly associated with early family income is in line with findings from previous research (e.g. Howe *et al.*, 2012).

[---FIGURE 2 HERE---

We turn now to the presentation of the estimates that examine the impact of different factors. We begin with a high level summary of the findings of our decomposition analysis, highlighting the differential treatment of proximal and distal factors in our framework. Subsequent tables focus on more disaggregated results. In all tables we present the path coefficients, which express the importance of the pathway in terms of the overall variation in the outcome (i.e. in standard deviation units). In selected tables we also express the coefficients as percentages of the total income gradient in each individual outcome. These latter percentages highlight the relative importance of different pathways in accounting for a

given gradient, but a small fraction of a large raw gradient may indicate greater disparities in real terms than a large fraction of a small gradient.

#### 4.2 *Summary decomposition of the role of proximal factors*

[---TABLE 1 HERE---

In terms of the model set out formally in Section 2 and Figure 1, Table 1 decomposes the raw income gradient according to:

$$\delta = \{\gamma(\beta\alpha + \lambda)\} + \{\theta\alpha + \pi\}$$

The first and second terms in the curly brackets above are the components of the gradient which are, and are not, explained by observed proximal variables respectively. Conceptually, proximal factors correlated with income must account for all of the gradients we observe. The decomposition in Table 1 shows the portion of the gradient explained by proximal factors we can observe (Row A) versus the portion generated by unobserved proximal factors (Row B). The sum of the contribution of observed and unobserved proximal factors is given in the final row and is a repeat of the raw relationships shown between income and the outcomes in Figure 2. The numbers in this table represent the total contribution of each proximal factor to the raw outcome gradients, and include pathways originating from all distal factors as well as from the direct contribution of income.

Row A shows that income-related differences in the observed proximal factors are associated with significant gradients in all six child outcomes. In size terms these are of similar magnitude for all outcomes except self-esteem and fat mass, where the predicted gradients are smaller. But when expressed as a share of the overall income gradient, the proximal influences capture a smaller share of the gradients associated with cognitive attainment (under 40%) than for the other outcomes. At the other extreme, 75% of the gradient in behaviour is explained. If we assume that all beneficial proximal processes, both observed and unobserved, are positively correlated (so that the omitted variable bias is always upwards) then these estimates are upper bounds on the extent to which the proximal factors measured in our data drive the observed income gradients. Under the extreme assumption that all the relationships estimated were causal, the results imply that if all differences in observed proximal factors between low- and higher-income families were eliminated, the income gradient in cognitive outcomes would fall by one-third, while the gradient in behaviour would fall by as much as three-quarters.

The next six sets of rows present the contributions of six sub-groupings of proximal influences. The poorer psychosocial functioning of low-income mothers (row i) is associated

with the income gradient for all six outcomes. But its strongest association, both in absolute and relative terms, is with self-esteem and behaviour, where it accounts for around 40% of the total unconditional income gradient. This is not due to maternal reporting of both child behaviour and her own mental health as the psychological scales in our data are completed by the mother for herself but by the teacher for the child.

Row ii shows that the patterns of pre-school childcare used by higher-income families are positively associated with IQ and locus of control but not with other outcomes. There is even some evidence that these same childcare patterns are negatively associated behaviour (although the path coefficient is only marginally significant). Differences in health-related behaviours contribute significantly to the gradients in all domains of development but, as we might expect, are of greatest importance for the fat mass gradient, where they account for over 60% of the total. The quality of the home learning environment is most strongly associated with deficits in cognitive and non-cognitive outcomes, but not at all associated with fat mass. The physical home environment accounts for little of the income gradients and, again, negative path coefficients for fat mass and self-esteem suggest the presence of protective factors in low-income families in this domain. We return to this protective effect in our detailed examination of the proximals in Table 3. Finally, differences in the schools attended by low- and higher-income children (as measured by school fixed effects) play no role in accounting for any of the gradients. This is suggestive that it is out-of-school environments (of which we have very detailed measures) that are the decisive influence on development to mid-childhood. It is possible that school effects may emerge later in the school career, after a longer period of exposure. In addition, the role of schools is estimated controlling for levels of neighbourhood deprivation, which are likely highly correlated with school type and may therefore absorb some of their effect. .

### ***4.3 Summary decomposition of the role of distal factors***

Table 2 looks at the role of the distal factors that are correlated with income in generating the raw income gradient. It ignores the proximal pathways and examine only how far the socio-demographic characteristics of low-income families can explain the observed raw income gradients. Estimates of the direct contribution of income are therefore comparable to reduced form OLS estimates of the effects of income on child outcomes (for example, Duncan and Brooks-Gunn, 1997, and many subsequent related papers).

Row A of the table shows this conditional role of income (i.e. through both observed proximal and unobserved proximals). It shows that the direct contribution of income to child

outcomes is significant only for cognitive outcomes, where it generates differences of 0.12 to 0.14 standard deviations for a log-point change in income. So around one-fifth of the raw gradient in cognitive outcomes reflects a direct contribution of income. The remaining 80% can be attributed to other distal factors than co-vary with low income and independently influence children's proximal environments. For the non-cognitive and fat mass outcomes no significant direct effect of income remains, although we note that in share terms it represent a large proportion of the deficit of low-income children in self-esteem. We return to these estimates in Section 4.6, where we explore how the direct contribution of income is mediated by different proximal factors.

[---TABLE 2 HERE---

The rest of Table 2 contains the pathways often not reported in other studies. These permit the direct contribution of income to be compared with the effect of the other correlated distal factors. Block B shows these in four sets: household demographics, labour market status of parents, education of parents and neighbourhood. Parental education (row iii) has a substantial influence on the income gradients in all the child outcomes. It accounts for over half the gradient in fat mass and for a quarter of the behavioural gradient, the outcome for which the proportion is lowest. The gradient in cognitive outcomes predicted by differences in educational attainment between low- and higher-income families is double the size of the direct income effect. These education pathways are likely to capture the role of unmeasured parental cognitive ability as well as qualifications. Education is also the only broad grouping of distal factors that significantly predicts gradients in all six outcomes.

Row ii shows there are substantial contributions of the differential labour market characteristics of parents (employment and occupation) to the cognitive, locus of control and behavioural outcomes even net of income and education, but this is not the case for self-esteem and fat mass. Row i shows a similar pattern for differences in household demographics associated with income, although the magnitudes of the path coefficients here are generally half the size of the those associated with labour market characteristics. Row iv shows there are also independent contributions from the local neighbourhood factors associated with income to cognitive and behavioural outcomes, with again no significant pathway to self-esteem. In contrast to the paths for household demographics and labour market status, we do find a significant and relatively large role for neighbourhood in predicting the fat mass gradient.

#### ***4.4 The role of specific proximal factors***

Table 3 disaggregates the associations in Table 1 and explores in more detail the gradients predicted by income-related differences in different proximal factors. These estimates are the separate  $\gamma_j(\beta_j\alpha + \lambda_j)$  paths. Row A of Table 3 and the totals for each block numbered i to vi repeat the information shown in Table 1. Within each block these combined paths are disaggregated into sub-sets of proximal variables which sum to the block total. We do not present shares in this table but the final row of the table shows the unconditional income gradients which are the denominators for such calculations.

[---TABLE 3 HERE---

Table 3 shows the following. First, a small set of proximal variables is associated with all, or almost all, of the aspects of child development we examine. The harsher discipline of low-income mothers, their more external locus of control, and their lower rates of breastfeeding are all associated with significant deficits in five of the six outcomes. Eating patterns at age 3, provision of books and toys and maternal teaching behaviours also contribute to multiple outcome gradients.

Second, specific proximals are associated with the income gradient in some outcomes but not others. The home learning environment is most strongly associated with the income gradients in the cognitive domain. Income-related differences in the books and toys and the maternal teaching experienced by pre-school children both predict poorer school performance and IQ at ages 7 and 8, even conditional on the many other detailed proximal controls. Lower fathers' learning-related interactions, allowing for maternal inputs, are associated with the poorer school performance of low-income children. Conversely, there are a number of factors that differ greatly between low- and higher-income families but that do not predict cognitive outcomes in any meaningful way, as is revealed by the large number of small, insignificant or off-setting path coefficients on factors such as the physical home environment. Our comparative approach shows that an exclusive focus on cognitive development could lead to the erroneous conclusion that certain factors do not significantly adversely affect the well-being of low-income children. The analysis shows that some factors that do not contribute to the cognitive gradients do appear consequential for other outcomes. Life events shocks, maternal social networks and exposure to smoke are associated with both behaviour and fat mass outcomes, and early childcare patterns are associated with later inequalities in locus of control and fat mass.

Third, the table identifies a number of instances in which the experiences of low-income children are relatively protective for their well-being (denoted by a negative gradient

coefficient). In some cases these negative gradients may reflect a high correlation between proximal factors coupled with an unmodelled interaction effect. For example, the negative path between educational trips and Key Stage 1 outcomes could arise because aspects of home learning environment are highly correlated and there are diminishing returns to these inputs among the most advantaged children. However, some effects suggest that behaviours of richer parents may actually harm their children. The lower exposure to centre-based childcare among low-income children aged three to four is associated with fewer behaviour problems (consistent with a number of previous studies, e.g. Belsky *et al.*, 2007). For fat mass, the negative coefficient for the physical environment proximal block is driven by two ‘off-setting’ factors: the lower probability of car access and the greater exposure to damp in the home among low-income children. It is plausible that both these factors lead to greater energy consumption, via more walking in the case of car access, and via the need to generate warmth (or possibly spend more time outdoors) in the case of homes that are cold and damp. The coefficient on the physical home environment block is of comparable magnitude but of opposite sign to the coefficient on eating patterns at age 3. This pattern suggests that greater energy consumption is partially ‘disguising’ the consequences of poor diet and other risk factors for obesity among low-income children, such that the fat mass gradient would be even steeper without its off-setting effect.

#### ***4.5 The role of specific distal factors***

Table 2 showed how far distal aspects of the family and parental characteristics contribute to the income gradients in outcomes. Table 4 explores these relationships in more detail, breaking down the summary measures of family characteristics into their constituent parts. Similar to the disaggregated analyses for proximal factors, Rows A, B and the block totals i to iv repeat the information from the summary Table 2, while the rows within each block provide path coefficients for sub-groupings of distal variables that sum to the block totals.

The household demographics block totals in row i show again that differences in these characteristics between low- and higher-income families contribute significantly to four of the six income gradients. But the breakdown below also shows that different aspects of this set of factors are associated with the outcomes in different ways. Results for family structure show that the greater rates of lone parenthood in low-income families contribute significantly to steeper income gradients in children’s behaviour problems, where the coefficient is comparable in size to the direct contribution of income. But there is no evidence that this is the case for the other outcomes and the negative coefficient in the IQ

decomposition implies that children of lone parents do better than expected, given their other disadvantages. The siblings row reveals almost the reverse pattern: the larger family size in low-income households contributes significantly to poorer cognitive development but is slightly protective for behaviour problems.

Block ii shows that in general it is the occupational status of low-income parents that is associated with poorer child outcomes, rather than whether or not they are actually in work. In fact, the uniformly negative (if small) coefficients for maternal employment imply that the lower employment rates of low-income mothers in the preschool period are slightly beneficial for children's development, all else (including income) held equal. Inspection of the component path coefficients (not shown here) reveals that it is the higher full time employment rates of higher income mothers that drive this off-set result.

The importance of parental education (net of income) in predicting child outcomes has already been shown. The results in block iii allow us to delve deeper and contrast the relative importance of maternal and paternal education and explore whether the qualifications of the child's maternal grandparents have any independent association. In general, the qualifications of both parents play a role. While the maternal education coefficients are slightly larger than the paternal ones for cognitive outcomes and locus of control, the reverse is true for the remaining outcomes, particularly fat mass. Significant contributions of grandparents' qualifications to four of the six gradients provide evidence of intergenerational transmission of human capital across three generations.

Within the neighbourhood block, residence in social housing has a particularly strong association with the gradients in school performance and in behaviour problems, but it also matters for IQ and self-esteem. Local area deprivation is associated with gradients in cognitive outcomes and fat mass, net of other distal influences, but does not contribute to the gradients in any of the non-cognitive outcomes.

[---TABLE 4 HERE---

#### ***4.6 How the direct contribution of income is mediated***

In Table 5 we return to an examination of the direct contribution of income (presented in Row A of Tables 2 and 4). In this decomposition we bring together the overlapping sets of distal and proximal factors to examine the pathways through which income is mediated. The decompositions in this table tell us about the ways in which money (separate from other parental characteristics) impacts on the proximal environment ( $\lambda_j$ ), and which of those paths



matter most for children's development ( $\gamma_j$ ). A residual part ( $\pi$ ) captures the influence of income via unobserved proximal factors, the part that remains unexplained. We use the term financial resources below when discussing the role of income in this more narrow direct sense, to help distinguish it from its role as a summary measure of social position. The results in this table correspond to the developmental psychology mediation studies such as Guo and Harris (2000), Schoon *et al.* (2010) and Yeung *et al.* (2002).

[---TABLE 5 HERE---

The top row of Table 5 presents the estimates of the direct income path presented above. The subsequent rows sum to these total contributions. Path coefficients that are less than 0.1 in magnitude (0.01 standard deviations of the outcome) and insignificant at the 10% level are omitted from the table. The percentages in square brackets represent the coefficient as a percentage of the direct contribution of income in the first row, *not* as a percentage of the overall income gradient as in previous tables. The total contributions shown in Table 1 combine the role of a proximal factor along two different pathways to the outcome – the direct income pathway and the ‘non-direct’ pathway via other associated distal factors, while the numbers in Table 5 isolate just the first of these. A comparison of the relevant percentages in the two tables, therefore, throws light on whether it is financial resources or other distal factors that are disproportionately associated with inequalities in each proximal grouping.

Table 5 shows that financial resources matter for cognitive outcomes via their association with the home learning environment, health behaviours and, to a lesser extent, via maternal psychosocial functioning. The percentages in the cognitive outcome columns are very similar to their counterparts in Table 1. For example, 33% and 42% of the direct income contribution to the IQ and Key Stage 1 gradients respectively is explained by observed proximal factors, and Table 1 shows that similarly 34% and 37% of the unconditional gradients are explained by the same factors. This implies that financial resources are no more, but also no less, important than other characteristics of low-income families in shaping the observed proximal factors that matter for cognitive development.

The picture is different when we look at other outcomes. Financial resources are disproportionately predictive of the aspects of psychosocial functioning that matter for behaviour problems and fat mass. The path coefficients associated with maternal psychosocial functioning are actually larger than the overall direct contribution of income to these two gradients, and are statistically significant where the overall coefficients (in the top

row) are not. The importance of the pathway from financial resources to maternal psychosocial functioning to behaviour and fat mass is partially ‘disguised’ in the aggregate estimates by other off-setting protective mechanisms associated with fewer financial resources (discussed below). Comparison of these percentages with those for the total raw gradients shown in Table 1 reveals that poorer psychosocial functioning accounts for much less, only around a third, of the unconditional gradients in behaviour and fat mass, implying that other distal factors such as education and family structure are less strongly linked to this mechanism (see also Propper *et al.*, 2007, who consider the link between income, maternal mental health and a range of children’s’ physical health outcomes). The same disproportionate influence of financial resources relative to other distal factors is also apparent in Table 5 for the patterns of childcare that matter for child locus of control and, to a lesser extent, the aspects of psychosocial functioning that matter for child self-esteem.

Table 5 reveals a number of instances in which greater financial resources are negatively associated with beneficial environments. The unconditional associations of higher income with patterns of child care that are problematic for behaviour, and with the physical environments that are problematic for fat mass, were discussed above. In addition, a significant pathway running from higher income to the home learning environment to greater fat mass emerges here (this pathway is of the same sign, but proportionately smaller and insignificant, as a component of the overall gradient in Table 1). We can speculate this result, like our findings on car access and damp in the home, indicates another mechanism through which lower income is associated with increased calorie expenditure and reduced obesity risk. It may be that the learning-focused environments common in more advantaged families place a greater weight on sedentary activities, while low-income children tend to engage in more active pursuits. In general, the significant coefficients and large percentages on a number of ‘off-setting’ paths in Table 5 imply that financial resources play an important role in contributing to these environmental differences, distinct from, say, higher education or better neighbourhood. The implication is that the inability of low income parents to afford certain goods and services actually benefits their children in terms of behaviour and fat mass.

Table 5 presents only one part of the complete overlapping decomposition made possible by our framework. Online appendix Table A4 contains the corresponding breakdowns for the four other distal contributions summarized in Tables 2 and 4. The results illustrate how our technique allows the examination of paths such as the link between parental education, the home learning environment and cognitive outcomes; the link between household demographics (including lone parenthood), psychosocial functioning and child

behaviour; and the link between neighbourhood, health behaviours and fat mass.

## **5. Discussion and conclusions**

This paper has examined the income gradients in cognitive, non-cognitive, and health outcomes in middle childhood, using a pathways approach informed by ecological models of child development. We exploit rich data on observed behaviours of parents and their characteristics. In contrast to many other studies, we examine six outcomes in a unified framework and allow for the uncertainty in estimates that results from missing data. Our approach allows us to compare the strength of the associations of family income across different outcomes and to explore how the pathways and confounding distal influences vary across the outcomes considered.

The results offer the following insights. First, we find that low-income children are disadvantaged across the full spectrum of developmental outcomes. The strongest gradients are in cognitive outcomes and the weakest in the health outcome of risk of obesity, with the gradients in non-cognitive outcomes lying in between. Second, certain factors appear consequential for children's development across the full spectrum of outcomes. In terms of distal factors, parental education accounts for at least a quarter, and in general much more, of the gradients in all six outcomes. Proximal factors that account for significant portions of the gradients in five of the six outcomes are harsh discipline, breast feeding and maternal locus of control. Third, despite the importance of some factors across all outcomes, we also find considerable evidence that the processes or pathways that are associated with income gradients in different outcomes are generally not the same. Aspects of low-income children's environments that are associated with poorer outcomes in one sphere often have no association, or even have an opposing association, with outcomes in other spheres. For example, less stimulating home learning environments and fathers' engagement in learning and larger family sizes predict far greater disparities in cognitive than in other outcomes. Gradients in children's self-esteem and behaviour problems are much more strongly linked to maternal psychosocial functioning, and to lone parenthood, than are gradients in cognitive or health outcomes. Maternal health behaviours are relatively more important for fat mass. Fourth, a large proportion of the social inequality shown by the raw income gradients is associated with the other distal characteristics of low-income families rather than simply a lack of financial resources. The direct (or conditional) association of income is insignificant for the four non-cognitive and health outcomes (although substantive in terms of magnitude

for self-esteem), and for cognitive outcomes amounts to around one-fifth of the total gradient. However, these aggregates can disguise certain paths in which financial resources play a substantial role, most notably for the maternal psychosocial characteristics such as anxiety and depression that are strongly on the path of child behaviour problems. Finally, we find indications that low income can, in some cases, act as a protective factor. For example lack of financial resources is associated with less exposure to childcare environments linked to problem behaviour and to home environments that lower the risk of obesity.

We have been careful to recognise the observational nature of our data and do not interpret the path coefficients as causal relationships. Nevertheless, we believe our results highlight lessons for research that seeks to quantify causal links. First, it is highly unlikely that a single experiment or trial could examine the causal nature of all the relationships allowed for by our model. Our findings provide some guide to which of the myriad possible mechanisms are most likely to be fruitful targets of intervention, and which have less chance of success. They thus help to refine the hypotheses that can be tested by expensive rigorous trials. Second, our results show that treating child human capital as a multi-dimensional vector can affect conclusions on the relative usefulness of different interventions. An intervention that has modest effects across multiple domains may turn out to be preferable to one that greatly improves one outcome but that has no or even adverse consequences in other domains. Increased exposure to certain types of childcare, for example, could boost cognitive outcomes but also increase behaviour problems. Greater learning-focused activities could decrease physical activity, with adverse consequences for health. On the other hand, interventions that increase mothers' sense of self-efficacy (locus of control) or discourage the use of harsh discipline, may lead to only small improvements in cognitive outcomes, but also have benefits in a number of other domains of children's development. So a recommendation that follows from our findings is that experiments should measure effects on as many outcomes as possible, even those that are not the primary target of the intervention, in order to get a rounded picture of the overall benefits.

Finally, if the aim of a policy is to reduce the income gradient, then knowledge only of which behaviours lead to positive outcomes (and so should be the target of manipulation) is not sufficient. As our method makes clear, the importance of a behaviour's contribution to the income gradient is the product of two relationships: the effect of the behaviour on the outcome, but also the extent to which that behaviour is concentrated among low-income families. If the factor targeted by the intervention is only weakly correlated with income, then outcomes may be boosted for children in general but there will be little narrowing in the

degree of inequality in outcomes. Again, recognizing this aspect of the broader consequences of an intervention may affect conclusions as to the costs and benefits of different options.

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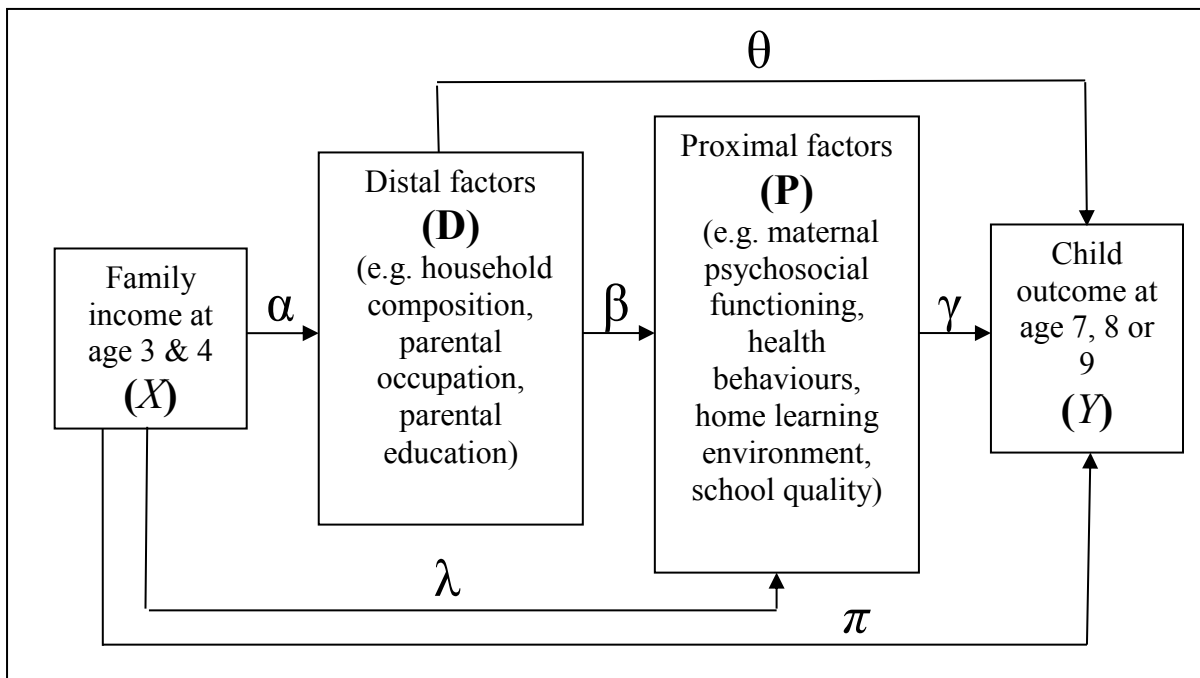
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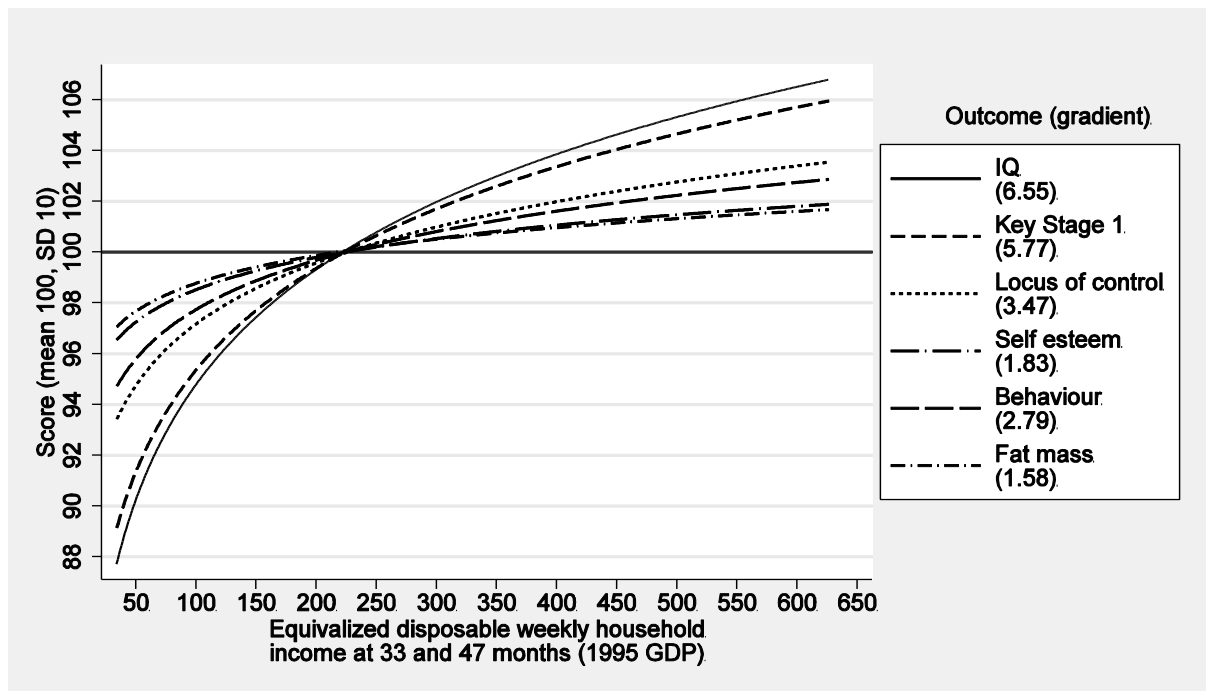


Figure 1. Income gradient decomposition path diagram



*Note.* The diagram represents a system of OLS equations in which the end point of an arrow is a (vector of) dependent variable(s), the beginning of the arrow is a (vector of) explanatory variable(s) and the Greek letters are the associated (vectors/matrices of) coefficients.

Figure 2. The income gradients in child outcomes in middle childhood



Notes. Higher scores reflect more favourable outcomes on all 6 measures. Gradients are  $\delta$  from the OLS regression:  $outcome_i = cons + \delta \ln(income)_i + e_i$ . All gradients statistically significant at the 1% level.

**Table 1. Summary decomposition 1: Contribution of proximal factors**

		Child outcome measure					
		Cognitive		Non-cognitive		Health	
		IQ	KS1	Locus of control	Self esteem	Behav- iour	Fat mass
A. Total contribution of proximal factors (sum i to vi): $\gamma(\beta\alpha + \lambda)$		<b>2.22**</b> [33.9%]	<b>2.16**</b> [37.4%]	<b>2.04**</b> [58.9%]	<b>0.80*</b> [43.8%]	<b>2.11**</b> [75.5%]	<b>0.93**</b> [59.2%]
i.	Maternal psychosocial functioning	0.55** [8.3%]	0.60** [10.3%]	0.51* [14.8%]	0.81** [44.4%]	1.09** [38.9%]	0.55** [34.9%]
ii.	Pre-school childcare	0.23* [3.6%]	0.09 [1.6%]	0.47** [13.6%]	-0.16 [-8.8%]	-0.25 <sup>†</sup> [-9.0%]	0.20 [12.7%]
iii.	Health & health behaviours	0.55** [8.3%]	0.66** [11.4%]	0.63** [18.1%]	0.06 [3.1%]	0.89** [31.9%]	0.95** [60.3%]
iv.	Home learning environment	0.67** [10.2%]	0.74** [12.7%]	0.42* [12.0%]	0.51** [27.9%]	0.37* [13.4%]	-0.27 [-17.0%]
v.	Physical home environment	0.14 [2.1%]	0.08 [1.4%]	-0.06 [-1.8%]	-0.43 <sup>†</sup> [-23.8%]	0.06 [2.0%]	-0.55* [-34.5%]
vi.	School fixed effects	0.09 [1.4%]	0.00 [0.0%]	0.08 [2.2%]	0.02 [0.8%]	-0.05 [-1.6%]	0.04 [2.8%]
B. Unexplained by proximal factors: $(\theta\alpha + \pi)$		<b>4.33**</b> [66.1%]	<b>3.61**</b> [62.6%]	<b>1.42**</b> [41.1%]	<b>1.03*</b> [56.2%]	<b>0.68</b> [24.5%]	<b>0.64</b> [40.7%]
Unconditional income gradient (A+B): $\delta$		<b>6.55**</b> [100%]	<b>5.77**</b> [100%]	<b>3.47**</b> [100%]	<b>1.83**</b> [100%]	<b>2.79**</b> [100%]	<b>1.58**</b> [100%]

Notes: N = 9476. Numbers in the higher row of each pair are the path coefficients shown in equation 5. Numbers in square brackets express the coefficient as a proportion of the unconditional income gradient given at the bottom of the table. All outcomes standardized to mean 100, standard deviation 10. Higher scores indicate more favourable outcomes on all measures. The unconditional income gradient is the difference in the outcome associated with a 1 unit change in the log of income. See online appendix Table A1 for definitions of all variables and contents of groupings. Standard errors (not shown) calculated by non-parametric bootstrap.

\*\* p<.01; \* p<.05; <sup>†</sup> p<.10.

**Table 2. Summary decomposition 2: Contribution of correlated distal factors**

	Child outcome measure					
	Cognitive		Non-cognitive			Health
	IQ	KS1	Locus of control	Self esteem	Behav- iour	Fat mass
A. Direct contribution of income: $\gamma\lambda + \pi$	<b>1.41**</b> [21.5%]	<b>1.15**</b> [19.9%]	<b>0.58</b> [16.6%]	<b>0.75</b> [40.9%]	<b>0.45</b> [16.1%]	<b>0.22</b> [14.1%]
B. Total contribution of distal factors (sum i to iv): $(\gamma\beta_k + \theta_k)\alpha_k$	<b>5.14**</b> [78.5%]	<b>4.62**</b> [80.1%]	<b>2.89**</b> [83.4%]	<b>1.08*</b> [59.1%]	<b>2.34**</b> [83.9%]	<b>1.36**</b> [85.9%]
i. Household demographics	0.55** [8.4%]	0.48** [8.3%]	0.38* [11.0%]	0.15 [8.0%]	0.32* [11.3%]	-0.18 [-11.7%]
ii. Labour market status	0.79** [12.1%]	0.94** [16.3%]	0.75* [21.7%]	0.23 [12.8%]	0.66* [23.8%]	0.12 [7.3%]
iii. Education	3.09** [47.1%]	2.05** [35.6%]	1.60** [46.2%]	0.58** [31.7%]	0.66** [23.5%]	0.88** [55.7%]
iv. Neighbourhood	0.72** [10.9%]	1.15** [20.0%]	0.16 [4.6%]	0.12 [6.6%]	0.71** [25.3%]	0.55* [34.5%]
Unconditional income gradient (A+B): $\delta$	<b>6.55**</b> [100%]	<b>5.77**</b> [100%]	<b>3.47**</b> [100%]	<b>1.83**</b> [100%]	<b>2.79**</b> [100%]	<b>1.58**</b> [100%]

See notes to Table 1. \*\* p&lt;.01; \* p&lt;.05; † p&lt;.10

**Table 3. Detailed decomposition 1: Contribution of proximal factors**

Path coefficient	Child outcome measure					
	Cognitive		Non-cognitive			Health
	IQ	KS1	Locus of control	Self esteem	Behav- iour	Fat mass
A. Total contribution of proximal factors (sum i to vi): $\sum_j \gamma_j(\beta_j\alpha + \lambda_j)$	<b>2.22**</b>	<b>2.16**</b>	<b>2.04**</b>	<b>0.80*</b>	<b>2.11**</b>	<b>0.93**</b>
<b>i. Maternal psychosocial functioning</b>	<b>0.55**</b>	<b>0.60**</b>	<b>0.51*</b>	<b>0.81**</b>	<b>1.09**</b>	<b>0.55**</b>
Of which:						
Maternal anxiety/depression	0.04	0.09*	0.10 <sup>†</sup>	0.16*	0.19**	-0.08
Life event shocks	-0.06 <sup>†</sup>	-0.01	0.02	0.05	0.16**	0.06 <sup>†</sup>
Subjective financial distress	0.06	0.12	-0.07	0.26	-0.04	0.20
Quality of parental relationship	-0.01	-0.13*	-0.07	-0.06	-0.22*	-0.07
Frequency of smacking at 3	0.09**	0.05**	0.09**	0.14**	0.11**	0.00
Maternal social networks	0.05	0.10	0.07	0.11	0.47**	0.19 <sup>†</sup>
Maternal locus of control	0.37**	0.37**	0.37**	0.14	0.43*	0.24*
<b>ii. Pre-school childcare</b>	<b>0.23<sup>†</sup></b>	<b>0.09</b>	<b>0.47**</b>	<b>-0.16</b>	<b>-0.25<sup>†</sup></b>	<b>0.20</b>
Of which:						
Birth to age 3	0.17	0.06	0.37**	0.00	0.04	0.25*
Age 3 to school entry	0.06	0.03	0.10	-0.16	-0.29	-0.05
<b>iii. Health &amp; health behaviours</b>	<b>0.55**</b>	<b>0.66**</b>	<b>0.63**</b>	<b>0.06</b>	<b>0.89**</b>	<b>0.95**</b>
Of which:						
Health at birth	0.08**	0.07**	0.03 <sup>†</sup>	0.03	0.03	-0.04*
Smoking	-0.18*	0.00	0.14	0.02	0.46**	0.39**
Breast feeding	0.24**	0.14**	0.17 <sup>†</sup>	0.00	0.22*	0.16 <sup>†</sup>
Eating patterns at 3	0.41**	0.45**	0.29*	0.02	0.19	0.45**
<b>iv. Home learning environment</b>	<b>0.67**</b>	<b>0.74**</b>	<b>0.42*</b>	<b>0.51**</b>	<b>0.37*</b>	<b>-0.27</b>
Of which:						
Books and toys	0.51**	0.35**	0.13	0.27*	0.30*	-0.14
Maternal teaching	0.16**	0.16**	0.04	0.12*	0.14*	-0.06
Maternal reading/singing	-0.11 <sup>†</sup>	0.00	0.02	-0.07	0.00	0.01
Paternal reading/singing	0.13	0.41**	0.18	0.10	0.04	-0.05
Trips to library, museums, etc	-0.02	-0.17**	0.04	0.08	-0.11	-0.04
<b>v. Physical home environment</b>	<b>0.14</b>	<b>0.08</b>	<b>-0.06</b>	<b>-0.43<sup>†</sup></b>	<b>0.06</b>	<b>-0.55*</b>
Of which:						
Car ownership	0.01	0.03	-0.02	-0.21	0.20	-0.33*
Has garden	-0.04	-0.04	-0.05	-0.06	-0.10	-0.01
Noise	0.04	0.03	0.05	0.00	0.10	-0.03
Crowding	0.18	0.07	0.10	-0.11	-0.06	0.00
Damp/condensation/mould	-0.05	-0.01	-0.14 <sup>†</sup>	-0.05	-0.08	-0.18**
<b>vi. School fixed effects</b>	<b>0.09</b>	<b>0.00</b>	<b>0.08</b>	<b>0.02</b>	<b>-0.05</b>	<b>0.04</b>
B. Unexplained by proximal factors: $\theta\alpha$	<b>4.33**</b>	<b>3.61**</b>	<b>1.42**</b>	<b>1.03*</b>	<b>0.68</b>	<b>0.64</b>
Unconditional income gradient (A+B): $\delta$	<b>6.55**</b>	<b>5.77**</b>	<b>3.47**</b>	<b>1.83**</b>	<b>2.79**</b>	<b>1.58**</b>
Observations	9476	9476	9476	9476	9476	9476

See notes to Table 1. \*\* p<.01; \* p<.05; <sup>†</sup> p<.1

**Table 4 Detailed decomposition 2: Contribution of correlated distal factors**

	Child outcome measure					
	Cognitive		Non-cognitive			Health
	IQ	KS1	Locus of control	Self esteem	Behaviour	Fat mass
A. Direct contribution of income: $\gamma\lambda + \pi$	<b>1.41**</b>	<b>1.15**</b>	<b>0.58</b>	<b>0.75</b>	<b>0.45</b>	<b>0.22</b>
B. Total contribution of distal factors (sum i to iv): $(\gamma\beta_k + \theta_k)\alpha_k$	<b>5.14**</b>	<b>4.62**</b>	<b>2.89**</b>	<b>1.08*</b>	<b>2.34**</b>	<b>1.36**</b>
i. Household demographics	<b>0.55**</b>	<b>0.48**</b>	<b>0.38*</b>	<b>0.15</b>	<b>0.32*</b>	<b>-0.18</b>
Of which:						
Family structure	-0.23*	0.06	0.03	0.14	0.46**	-0.15
Siblings	0.40**	0.33**	0.07	0.16*	-0.14 <sup>†</sup>	-0.08
Mother's age at birth	-0.01	-0.02	-0.06**	-0.05	0.01	-0.02
Ethnicity	0.38**	0.10 <sup>†</sup>	0.33**	-0.10	-0.02	0.07
ii. Labour market status	<b>0.79**</b>	<b>0.94**</b>	<b>0.75*</b>	<b>0.23</b>	<b>0.66*</b>	<b>0.12</b>
Of which:						
Mother's employment	-0.13*	-0.11*	-0.12	-0.12	-0.10	-0.06
Father's employment	-0.09	0.07	0.03	0.17	0.13	0.07
Mother's occupation	0.33**	0.38**	0.44**	0.08	0.17	0.16
Father's occupation	0.69**	0.61**	0.47**	0.10	0.46*	-0.05
iii. Education	<b>3.09**</b>	<b>2.05**</b>	<b>1.60**</b>	<b>0.58**</b>	<b>0.66**</b>	<b>0.88**</b>
Of which:						
Mother's qualifications	1.44**	0.97**	0.81**	0.13	0.23	0.22
Father's qualifications	1.27**	0.95**	0.58*	0.43*	0.36	0.43**
Grandparents' qualifications	0.38**	0.14*	0.21**	0.02	0.08	0.23**
iv. Neighbourhood	<b>0.72**</b>	<b>1.15**</b>	<b>0.16</b>	<b>0.12</b>	<b>0.71**</b>	<b>0.55*</b>
Of which:						
Local deprivation	0.24**	0.27**	0.02	-0.18	-0.17	0.23*
Housing tenure	0.47**	0.88**	0.14	0.30 <sup>†</sup>	0.88**	0.31
Unconditional income gradient (A+B): $\delta$	<b>6.55**</b>	<b>5.77**</b>	<b>3.47**</b>	<b>1.83**</b>	<b>2.79**</b>	<b>1.58**</b>

See notes to Table 1. \*\* p<.01; \* p<.05; <sup>†</sup> p<.1

**Table 5. Decomposition of the direct contribution of income**

	Child outcome measure					
	Cognitive		Non-cognitive			Health
	IQ	KS1	Locus of control	Self esteem	Behaviour	Fat mass
Direct contribution of income : $\gamma\lambda + \pi$	<b>1.41**</b>	<b>1.15**</b>	<b>0.58</b>	<b>0.75</b>	<b>0.45</b>	<b>0.22</b>
	[100%]	[100%]	[100%]	[100%]	[100%]	[100%]
Of which explained by: $(\gamma_j\lambda_j)$						
Maternal psychosocial functioning	0.12	0.17 <sup>†</sup>	0.10	0.42**	0.54**	0.34**
	[8.4%]	[14.4%]	[17.7%]	[56.0%]	[120.3%]	[152.5%]
Pre-school childcare	-	-	0.22*	-0.11	-0.23*	-
			[38.8%]	[-14.7%]	[-51.0%]	
Health & health behaviours	-	0.16**	0.11 <sup>†</sup>	-	0.15 <sup>†</sup>	-
		[14.1%]	[19.1%]		[32.5%]	
Home learning environment	0.13*	0.11*	-	0.16*	-	-0.14*
	[9.1%]	[9.5%]		[21.7%]		[-63.2%]
Physical home environment	-	-	-	-0.13	-	-0.17*
				[-17.4%]		[-75.3%]
School fixed effects	-	-	-	-	-	-
Unexplained: $\pi$	0.94**	0.66**	-	0.25	-0.12	0.11
	[66.5%]	[57.6%]		[33.5%]	[-26.3%]	[50.2%]

Notes: N = 9476. Numbers in the higher row of each pair are selected path coefficients shown in equation 5. Numbers in square brackets express the coefficient as a proportion of the direct contribution of income given in the first row of the table. Standard errors (not shown) calculated by non-parametric bootstrap.

\*\* p<.01; \* p<.05; <sup>†</sup> p<.10.